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Unmanning UAVs – Addressing Challenges in On-Board Planning and Decision Making

Pritesh Narayan, Paul Wu, Duncan Campbell

Australian Research Centre for Aerospace Automation (ARCAA)
Queensland University of Technology
2 George St, Brisbane, Australia
da.campbell@qut.edu.au

Abstract. Planning and decision making, especially the planning of dynamically negotiable collision free paths, is an integral part in the operation of Unmanned Aerial Vehicles (UAVs). Effective path planning ensures that the UAV operates safely, and conforms to the rules and regulations governing flight within the National Airspace System (NAS). To demonstrate an Equivalent Level Of Safety (ELOS) to that of piloted aircraft for certification purposes, UAVs must demonstrate a high level of autonomy without a human in the loop. This research surveys the literature as to how human experts perform planning tasks and forms a framework which promotes shared authority of UAV mission (re)planning and path planning, and can adopt sole authority should the UAV communications link fail or the human operator relinquishes decisions. It has been demonstrated through simulation that the optimization of flight manoeuvre sets using multiple objectives allows for convergence to a solution which better represents civilian mission requirements whilst emulating common flight patterns of trained pilots. These initial findings highlight the challenges involved in replicating the skills of human pilots onboard a UAV. It is revealed that UAV planning and decision making is a multi-disciplinary problem that combines the fields of path planning (search optimization), trajectory generation, and human cognition

1 Introduction

Unmanned Aerial Vehicles (UAVs) have been employed, with great effectiveness, in a diverse range of military applications. However, geographically sparse countries, such as Australia, have great potential for utilization of UAVs in a wide range of civilian applications. These include asset management, search and rescue, and remote sensing. In order to realise this potential, it is necessary to gain access to the National Airspace System (NAS).

Operation of UAVs in the NAS creates a set of challenges not applicable to many military applications. From a regulatory perspective, UAVs need to: (i) demonstrate an Equivalent Level Of Safety (ELOS) to that of a human piloted aircraft, (ii) operate in compliance with existing aviation regulations and (iii) appear transparent to other airspace users [1]. Additionally, for the majority of current UAV operations, the human operator acts as both the mission manager and the pilot using a real time communications link [2]. This results in high operator workload and places great reliance on the communications link.

Path planning assists in ensuring that the flight is operated in accordance with the rules of the air. The inclusion of automated planning systems onboard can potentially improve mission efficiency and reduce the need for laborious input from a ground-based human operator. This avoids problems associated with communications link failures and operator fatigue. UAV path planning can be considered in terms of global (mission) planning and local (trajectory) planning. This paper outlines the challenges involved in both types of planning and reviews studies on how human pilots currently perform these tasks. In light of these findings, candidate planning algorithms are identified to replicate human planning and decision making.

2 Global Planning

Global planning is concerned with finding a flight plan that minimises a cost function. Flight plans typically follow the standard profile shown in **Fig. 1**. The en-route flight plan comprises a series of waypoints, assumed to be joined by straight line trajectory segments, originating at the climb phase just after takeoff and terminating at the descent phase prior to approach. For the purposes of this paper, it is assumed that the UAV operates under Visual Flight Rules (VFR) as many civil applications (e.g. crop dusting) are performed under VFR [3].

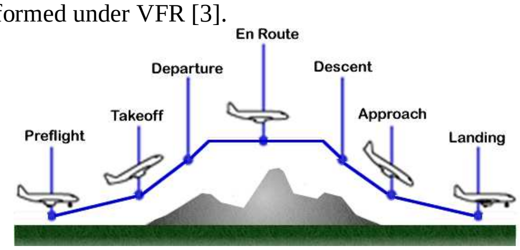

Fig. 1. Standard flight profile [4]

2.1 Path Planning and Sequential Decision Making

It has been shown that the path planning problem is of PSPACE complexity [5]. This complexity arises due to the exponential increase in memory and computation time with dimensionality. In 3D flight planning, the problem is further compounded by the size of the search space (due to the flight range of UAVs) and the need to optimise for multiple objectives (such as fuel, risk and rules of the air) [6]. Therefore, it is of value to study and replicate the cognitive skills of human expert pilots given their proficiency at flight planning [7]. Conventional path planners are complex, incomplete and computationally costly [8]. Replication of decision strategies (as opposed to direct replication of human knowledge which is difficult [9]) of human experts can help create a planning framework that is more efficient. Additionally, this provides a high degree of cognitive compatibility which increases the system's usefulness in terms of design and operation.

The flight planning problem can be modelled as a sequential decision process where actions are chosen to maximally satisfy multiple designated objectives [5, 8]. These decisions are not independent as later decisions are constrained by earlier decisions. Furthermore, the decisions need to be made in real time [8].

Typical path planning methods model this sequential decision process through the dynamic programming recurrence equation [5]:

$$g\left(s_{k+1}\right) = g\left(s_k\right) + c\left(s_k, s_{k+1}\right) \tag{1}$$

where $s \in S$ is a node in the 3D search space, s_{k+1} is a child node to s_k (the parent), g is the total cost to reach a node from the start node s_I, and $c(s_k,s_{k+1})$ is the edge cost, i.e. the transition cost of moving from s_k to s_{k+1}. Methods such as A* iteratively evaluate nodes in the search space and calculate the cost g to neighbouring nodes until the minimum cost g^* for the goal node s_g has been found. From (1), it can be seen that the cost of each node s is a summative accumulation of individual decision outcomes from the start node.

Ideally, the multi-objective sequential decision making process should be conducted in decision space (which includes, in addition to x, y, z, variables like fuel and risk). Unfortunately, this is computationally challenging on small aircraft due to the PSPACE complexity of path planning [5]. It is common practice (e.g. [10, 11]) to "aggregate" the decision variables into a single cost variable. Thus, the optimal path is in actuality the least aggregated cost path.

However, the majority of human pilots, when equipped with the appropriate decision interface, are capable of planning satisficing paths that are at worst 5% more expensive from an "optimal" path generated by a computer [8]. Therefore, it is instructive to examine the cognitive strategies of human pilots for the purpose of flight planning.

2.2 Pilot Decision Model

It has been found that human pilot decision making can be described with 'non-rational' or naturalistic decision making models [12]. This form of decision making is characterised by the concept of *bounded rationality* [13]. Studies have shown that humans characteristically focus only on three to four categories of attributes (less than ten variables), adopt *non-compensatory* decision strategies (especially when under duress), and process only a few decision alternatives [14].

Additionally, studies have revealed that expert pilots predominantly employ intuition based decision making but also include some elements of analytical decision making

[9]. Intuition can be defined as "knowledge based on experiences and acquired through sensory contact" [9]. One way of characterising this form of decision making is through the *Recognition Primed Decision Making* (RPDM) model. This model is in actuality an intuitive form of diagnosis and prediction which can be surmised as (i) recognition (pattern matching), (ii) serial evaluation (generating situational awareness) and (iii) mental simulation. Thus, the expert pilot employs pattern matching using experience honed cues (effectively a form of *a priori* knowledge) to structure the decision process. This then activates conditional IF THEN rules which produce the final decision outcome [9, 12].

It has been observed that human pilots frequently make use of rules and procedures in their decision making processes [7, 9, 12]. This in part stems from the vigorous training of procedures and aviation rules. Additionally, human pilots also manage the weighting and selection of rules, attributes and even search cues based on the overall situational awareness; this is known as meta-cognition [12, 15]. Rasmussen's model [16] provides a holistic framework that captures both the RPDM and meta-cognitive elements of human pilot cognition. The CASSY [17] aviation decision support system is based on Rasmussen's model.

Using Rasmussen's model, the decision making component (each evaluation of (1)) of the flight planning task can be described as shown in **Fig. 2**. At each increment in the flight plan, decision variables are extracted from sensor data, Geographic Information Systems (GIS), weather and air traffic information and from the aggregated cost of previous decisions $g(s_k)$. These variables form the antecedents for IF THEN rules for RPDM and meta-cognition. Therefore, the cost function needs to be a multi-objective evaluation function capable of implementing multiple rules in a hierarchical manner. A candidate method for this would be fuzzy inferencing [6].

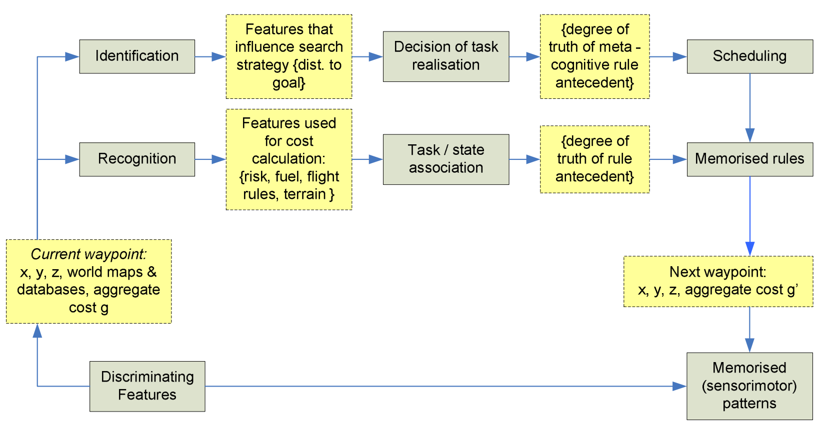

Fig. 2. Rasmussen's 3 layer model [16] depicted as a data flow diagram for flight planning

An important component in the decision making process above is the use of heuristics. Human pilots often employ heuristics, a category of cognitive processes whose primary role is to reduce the search space and thus speed up the decision process [12]. The heuristic is a meta-cognitive approach that can be used to prioritise the sequential decision process (i.e. choose which regions of the search space to explore first). Some heuristics, such as representativeness, availability and bias can adversely affect the solution outcome [18]. A useful heuristic, however, is adjustment and anchoring. With this heuristic the search process is seeded with an initial guess which is then adjusted based on available situational awareness information. Adjustment and anchoring is well suited to flight planning as flight plans predominantly follow the standard flight profile as shown in **Fig. 1** [18].

The anchoring and adjustment heuristic can be implemented with a heuristic search algorithm such as A*. In A*, the search process is prioritised according to a heuristic cost term:

$$f(s) = g(s) + h(s, s_g) \tag{2}$$

where h is a heuristic estimate of the cost to go from s to the goal s_g and f is the total cost (s_I to s_g). Therefore, through careful selection of h, it is possible to bias the search towards the standard flight profile.

2.3 Using Cognitive Techniques in Path Planning

The previous review of literature concerning pilot decision making has established three key points: (i) pilots tend to find a satisficing rather than an optimal path, (ii) pilots employ pattern matching (IF THEN rules, or production rules [9]), and (iii) heuristics aid in culling the search space. Therefore, heuristic search algorithms such as A* can be used as a suitable starting point for replicating human pilot planning. These algorithms have been used extensively in mobile robotics [19]. However, anytime replanning variants of A*, such as ARA*, are even better suited as, through adjustment of a heuristic inflation factor ε, it is possible to quickly find a satisficing solution. Furthermore, the solution path has a total cost of at most ε-times the optimal path cost [20]. Thus, if time is available, it is possible to iteratively decrease ε until ε<1 which gives the optimal solution.

Fig. 3 depicts an implementation of A*, showing a solution path in a complex environment. The decision variables for this investigation, based on VFR operation, are: (i) altitude Above Ground Level (AGL), (ii) airspace type, (iii) population risk (fatality risk per flight hour presented to people on the ground [21]), (iv) fuel consumed, and (v) weather (wind and storm cells). The search algorithm uses the framework presented in [6] for integrating a multi-criteria cost function into a path planner.

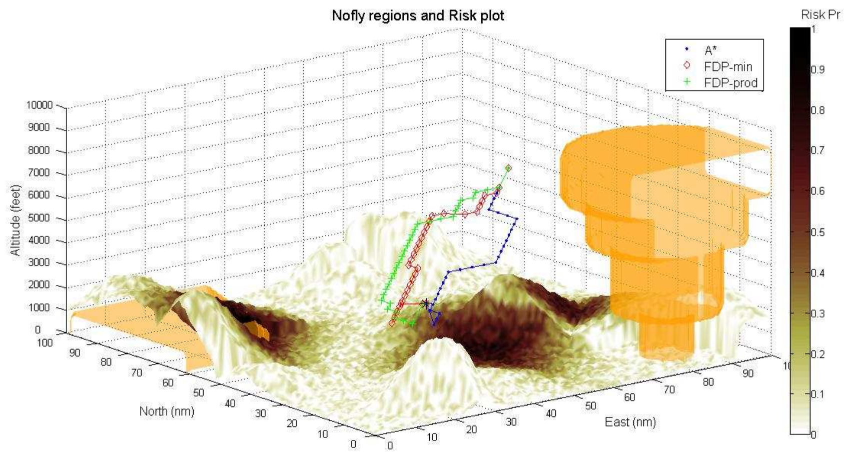

Fig. 3. Example flight paths using A*, Fuzzy Dynamic Programming (FDP) with min t-norm, and with product t-norm. Controlled airspace, and population risk shown.

The problem with A* like algorithms is identified in (1). The summative aggregation of prior decision outcomes means that decisions are aggregated using a disjunctive operator [22]. Therefore, as is highlighted in **Fig. 3**, there are cases where A* chooses a path with highly undesirable segments (i.e. high incremental cost) because the resultant summed cost is low. Oftentimes, it is desirable to avoid these high incremental cost paths unless if no other alternatives exist.

One method for addressing this shortcoming is to employ Fuzzy Dynamic Programming (FDP) [22]. Here, the sequential decision process is tracked using a conjunctive or t-norm operator:

$$\mu_{G_{i+1}}\left(x_{i+1}\right) = \max_{u_i}\left(\mu_{C_i}\left(u_i\right) \wedge \mu_{G_i}\left(x_i\right)\right) \quad \textbf{(3)}$$

At each decision step along a path, the utility value $\mu_G\left(x_{i+1}\right)$ of a state x_{i+1}, is found by the t-norm ($\wedge$) of the parent utility value $\mu_{G_i}\left(x_i\right)$, and the state transition action u_i, that gives maximal $\mu_G\left(x_{i+1}\right)$. The transition action u is transformed into a utility value using a constraint Membership Function (MF) $\mu_{C_i}\left(u_i\right)$. Note that fuzzy dynamic programming is cast in terms of a utility value, which is simply the negative of the cost.

Two FDP t-norm operators are evaluated against A* - the min and the product operators. The resultant paths are also shown in **Fig. 3**; note these paths avoid the higher risk regions. Over a number of simulations, it is unsurprising to find that the FDP methods find paths with lower maximum incremental path costs (**Fig. 4**). However, when using the min t-norm, the solution paths are significantly longer. This occurs because the min operator is more pessimistic and does not allow for compensation between the constraints and the goals [22]. On the other hand, the product operator tends to find paths with a better balance between incremental path cost and path length. Unfortunately, both FDP methods take longer computation time than A*, and this is due to the fact that the current FDP framework doest not include a heuristic component to guide the search.

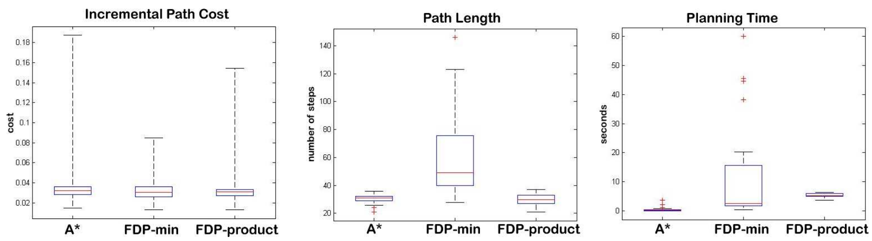

Fig. 4. Box and whiskers plots, showing inter-quartile range for incremental path costs, path length, and planning time

This preliminary investigation into automation of UAV flight planning has revealed that there are benefits in replicating human expertise. A survey of existing studies on human pilot cognition reveals that pilots predominantly rely on RPDM (pattern matching) and heuristics. This can be modelled specifically for flight planning using an adaptation of Rasmussen's three layered cognitive model. In turn, this sequential decision model can be replicated using A* or fuzzy dynamic programming; by using a product t-norm operator, a path that mimics human expectations is found. However, there remain many challenges that need to be addressed. These include evaluation of suitable multi-criteria cost functions (e.g. [6]), study of suitable heuristics and incorporation of heuristics into fuzzy dynamic programming. Unlike A*, the existing fuzzy dynamic programming framework does not include a heuristic term (3).

3 Local Planning

Local planning provides a navigation strategy for safe traversal through cluttered environments. This can be represented as a collision free flight trajectory which ensures that the platform remains within performance bounds. The implementation of local planning systems onboard UAV platforms has numerous benefits including overcoming potential ground station link issues. However, automating the local planning process is non-trivial and some challenges include: incorporation of complex platform dynamics, optimisation of trajectory to meet mission requirements, real-time constraints on computation time imposed by obstacles in the flight path, and the guarantee that trajectories generated are collision free. The following section presents a brief overview on flight trajectory representation.

3.1 Flight Trajectory Representation

A flight trajectory typically represents the desired motion of the aircraft during transversal between two points in airspace (i.e. current and goal position). The inclusion of vehicle dynamics during the trajectory planning process, allows for the generation of flight trajectories which take platform constraints into account.

Vehicle dynamics are used to calculate the performance envelope which the aircraft must remain within to ensure vehicle stability during flight. The types of aircraft performance bounds which can be included during the trajectory planning process is dependent on the number of states used for trajectory representation (e.g. position, velocity, acceleration, attitude, attitude rates). A 3 Degree Of Freedom (DOF) trajectory representation can allow for the inclusion of multiple aircraft performance bounds including: min (stall) and max velocities, min turn radius, and max climb and descent rates. However, a more complex 6 DOF trajectory representation is required for the inclusion of attitude rate constraints (e.g. max roll rate).

An example of flight trajectory representation is through the use of polynomial or spline based techniques [23, 24], where control points can be placed in a certain order to generate the desired trajectory. The use of polynomial or spline curve approximation limits trajectory representation to only 3 DOF. Without attitude and attitude rate state information, it is not possible to guarantee that the aircraft motion remains within platform performance bounds; in particular, the attitude rate constraints.

3.2 Trajectory Generation using Manoeuvre Automaton Theory

Manoeuvre Automaton theory is a published approach [25], where smooth feasible flight trajectories are formed via concatenation of predefined trim and manoeuvre primitives. Generating trajectories using manoeuvre automaton theory allows the inclusion of attitude information (roll, pitch and yaw) for trim manoeuvres and attitude rate information for manoeuvre primitives. This ensures that the trajectory generated is within vehicle performance bounds. Furthermore, trim and manoeuvre primitives can be configured to emulate flight manoeuvres performed by trained pilots (e.g. coordinated turn). The following sections outlines the implementation of manoeuvre automaton theory to generate smooth trajectories for fixed wing UAS in 3D space.

3.2.1 Trim Primitives

Six predefined trim primitives (referred to as flight modes) have been implemented in simulation including: cruise; flat turn, climb, descent, helical climb and helical descent. The flight dynamics model is based on the Aerosonde UAV data set available in the Aerosim Blockset [26].

3.2.2 Transition Primitives

A transition primitive has been implemented to ensure that the platform remains with performance boundaries while switching between flight modes. The UAV platform dynamic model is propagated until the UAV reaches the desired state configuration for execution of the next flight mode. The transition manoeuvre required to switch from cruise to coordinated turn flight modes in shown in **Fig. 5.**

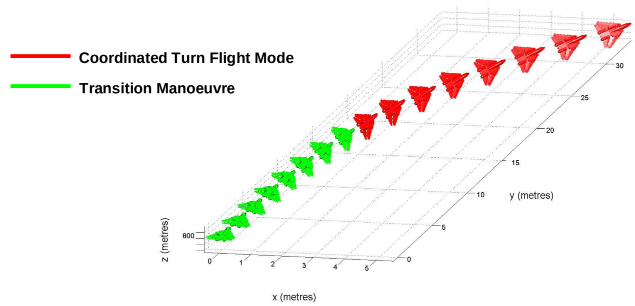

Fig. 5. Transition Manoeuvre Linking Cruise and Coordinated Turn Flight Mode

3.3 Trajectory Optimisation

Dynamic programming has been previously employed in related research [27, 28, 29] for the optimization of feasible trajectories that have been generated using manoeuvre automaton theory. Dynamic programming is a sequential optimization process and is appropriately suited to this particular optimization problem (referred to as manoeuvre generation) since only one flight mode can be executed at any one time.

Traditionally, trajectory generation techniques converge to near/optimal solutions by minimizing a singular cost function (e.g. fuel, time, distance). However, during each mission; civilian UAS may have multiple objectives to meet including platform safety; successful completion of the mission; minimizing fuel, time, and/or distance; or minimizing deviation from the current path. The use of multi-objective optimization allows the generation of a solution may better reflect the overall requirements of the mission.

The manoeuvre generation process was implemented in simulation using MATLAB to demonstrate how the inclusion additional objectives can potentially lead to the generation of trajectories which better represent overall mission requirements. A 3D environment representation was setup to simulate an urban scenario, where the UAV assignment included safe and efficient navigation through a predefined set of waypoints.

3.3.1 Single Objective Optimisation

To ensure mission completion; single objective optimization of trajectories generated through manoeuvre generation have been limited to distance minimization. Essentially, the optimal solution (per iteration) is the candidate flight manoeuvre which, once executed, minimizes the distance required to travel to the goal.

Simulated results for a single objective manoeuvre generation scenario are presented in (**Fig. 6)**.

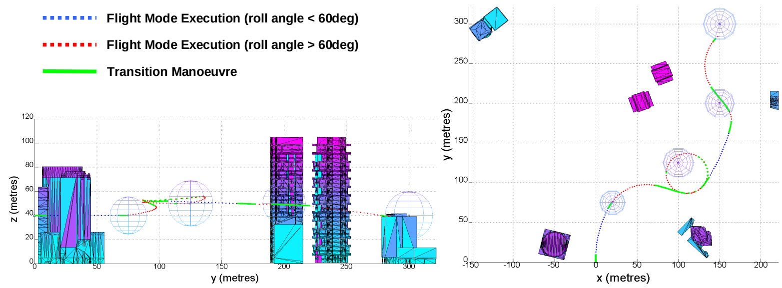

Fig. 6. Simulated Results for 3D Manoeuvre Generation using single objective optimisation

Single objective optimization during manoeuvre generation only considers the distance remaining to goal after flight mode execution. This may lead to the generation of trajectories which do not adequately satisfy mission requirements. For example, the trajectory generated in simulation (**Fig. 6)** requires the execution of flight modes approaching the performance limits of the platform; placing the vehicle at greater risk to loss of controllability. Thus, the solution generated may not be deemed acceptable if flight safety was an important mission requirement. The inclusion of additional objectives during the optimization process can potentially provide a better representation of overall mission requirements. The following section presents simulated results for multi-objective optimization of manoeuvre generation with respect to civilian operations.

3.3.2 Multi-Objective Optimisation

Loss of platform control can potentially result in collision with the surrounding environment. The consequences may be greater if UAV operations are undertaken in populated regions. Thus, operations in populated environments may benefit from the inclusion of objectives place a greater emphasis on safety by minimizing platform control loss during manoeuvre generation.

Two additional objectives have been included in the optimisation process of the simulated urban scenario to generate trajectories which are less likely to lead to loss of platform control. These objectives include: minimizing wing loading; and minimizing transition length required to execute next flight mode. The wing loading minimization objective gives a greater utility value to candidate flight modes which maintain a lower roll angle during execution since more controller power is available to recover from unexpected disturbances (e.g. wind gust). The transition length minimization objective gives a greater utility value to candidate flight modes which require shorter transition manoeuvres before execution, thus potentially decreasing platform instability due to coupling between lateral and longitudinal responses [30].

Fig. 7 presents simulated results after the inclusion of wing loading minimization objective to the single objective optimization process. Additionally, **Fig. 8** presents simulated results for the inclusion of transition length minimization to the single objective optimization process. Finally, **Fig. 9** presents simulated results for the inclusion of both objectives to the optimisation process.

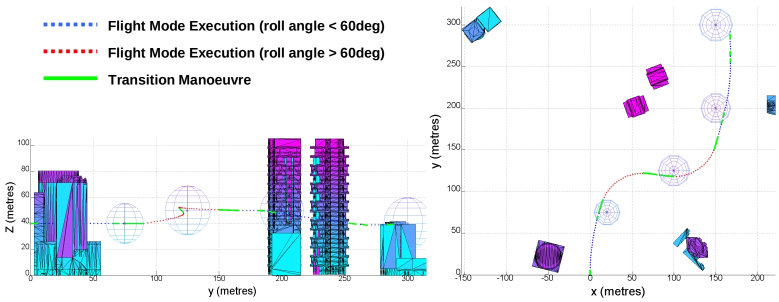

Fig. 7. Inclusion of wing loading minimization objective to optimisation process

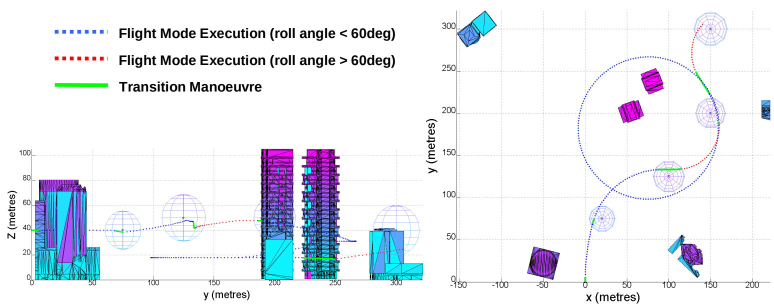

Fig. 8. Inclusion of transition length minimization objective to optimisation process

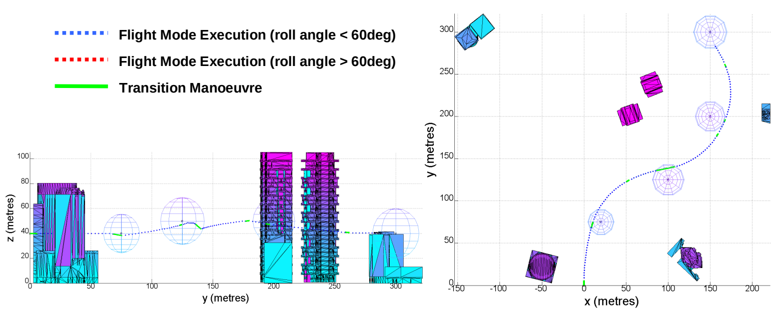

Fig. 9. Inclusion of wing loading and transition length minimization objectives

4 Conclusions

The research presented in this paper demonstrates the multi-disciplinary nature of UAV planning and decision making. Despite the complexity of flight planning and trajectory generation, human pilots perform such tasks with proficiency. A survey of existing studies on human pilot cognition revealed that human cognition can be modelled using Rasmussen's three layered structure. The paper presented some initial findings in replicating this model using A* and fuzzy dynamic programming. Additionally, it has been shown through simulation that optimization of flight manoeuvres can be used to emulate common flight patterns of trained pilots. Inclusion of multiple objectives mimicking human decision making results in trajectories that better match mission requirements.

This initial work presented here paves the way for future research into replication and modelling of human cognition with planning algorithms for UAV operation. Future work includes evaluation of suitable multi-criteria cost functions, study of suitable heuristics and incorporation of heuristics into fuzzy dynamic programming.

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